FAULT DETECTION FOR DISTILLATION COLUMN USING MULTIVARIATE STATISTICAL PROCESS CONTROL (MSPC)

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ABSTRACT

Chemical process is inclined to be a large-scale, complex and having stringent requirements on the desired quality. It also utilizes a lot of energy, must be environmentally friendly and fulfill safety requirements. Accurate process fault detection at an early stage of the process is important to modern chemical plant in achieving the above requirements. This paper focuses on the application of Multivariate Statistical Process Control (MSPC) as a fault detection tool. An industrial distillation column is modelled and chosen as the case study for this research. Principal Component Analysis (PCA) and Partial Correlation Analysis (PCorrA) are used to develop the correlation coefficients between the variables of the process. Faults considered in the research are sensor failures, valve failures and controller malfunctions. Shewhart Control Chart with the developed correlation coefficients are used for detecting the faults. Results show that both methods based on PCorrA and PCA are able to detect the pre-designed faults.

Keywords: correlation coefficient; partial correlation analysis; principal component analysis

1.0 INTRODUCTION

Currently, many chemical processes are becoming increasingly measurement rich. Large volume of highly correlated data is always recorded. This large volume of data can be very useful for process monitoring if an appropriate analysis method is applied (Lam and Kamarul, 2002a). Multivariate Statistical Process Control (MSPC) is a method that is able to extract the desired information from the data by carrying out data reduction without losing the original information. Many industrial processes involve a set of input variables and quality variables, which are highly correlated. If one of the variable changes, it will affect the other correlated variables (Lam and Kamarul, 2002b). Thus, ignoring the cross-correlation between the variables can lead to misinterpretation of the process behaviour.

One advantage of MSPC is that this method could reduce the complexity of online process monitoring with its ability to detect process abnormalities that are difficult to notice. Principal Component Analysis (PCA) is used to extract the required information for process monitoring from the data of the process. Partial Correlation Analysis (PCorrA) will also be used in this work for information extraction of the original data. PcorrA is a method that is able to determine the correlation between two variables while maintaining other correlated variables at a constant value (Kamarul, 1995). In MSPC, the correlation between variables is the major information needed for good process monitoring performance. In Lam and Kamarul (2002b), the cross-correlation coefficients between process variables were introduced as tool for process monitoring for fault. In this research, PCA and PCorrA will derive the cross-correlation coefficients from data collected from the simulation model.

Shewhart Control Chart is plotted using the developed correlation coefficients from PCA and PCorrA for process monitoring of the process. The function of these control charts is to compare the current state of the process with "Normal Operating Condition (NOC)". NOC exists when the process variables and quality variables remain close to their desired values. In contrast, "Out of Control (OC)" occurs when fault appears in the process. OC exists when one or more value of the quality variable and the input variable are outside the control limit of their respective control chart.

2.0 PROCESS MODELLING AND DATA GENERATION

Data mining is the most important part in obtaining an accurate correlation between the process variables and quality variables. In this research, data is obtained from a simulation model. A distillation column from a Palm Oil Fractionation Plant is selected as the case study. The model of this column is developed based on the model by Wong (2003). Figure 1 shows the process and the key variables.

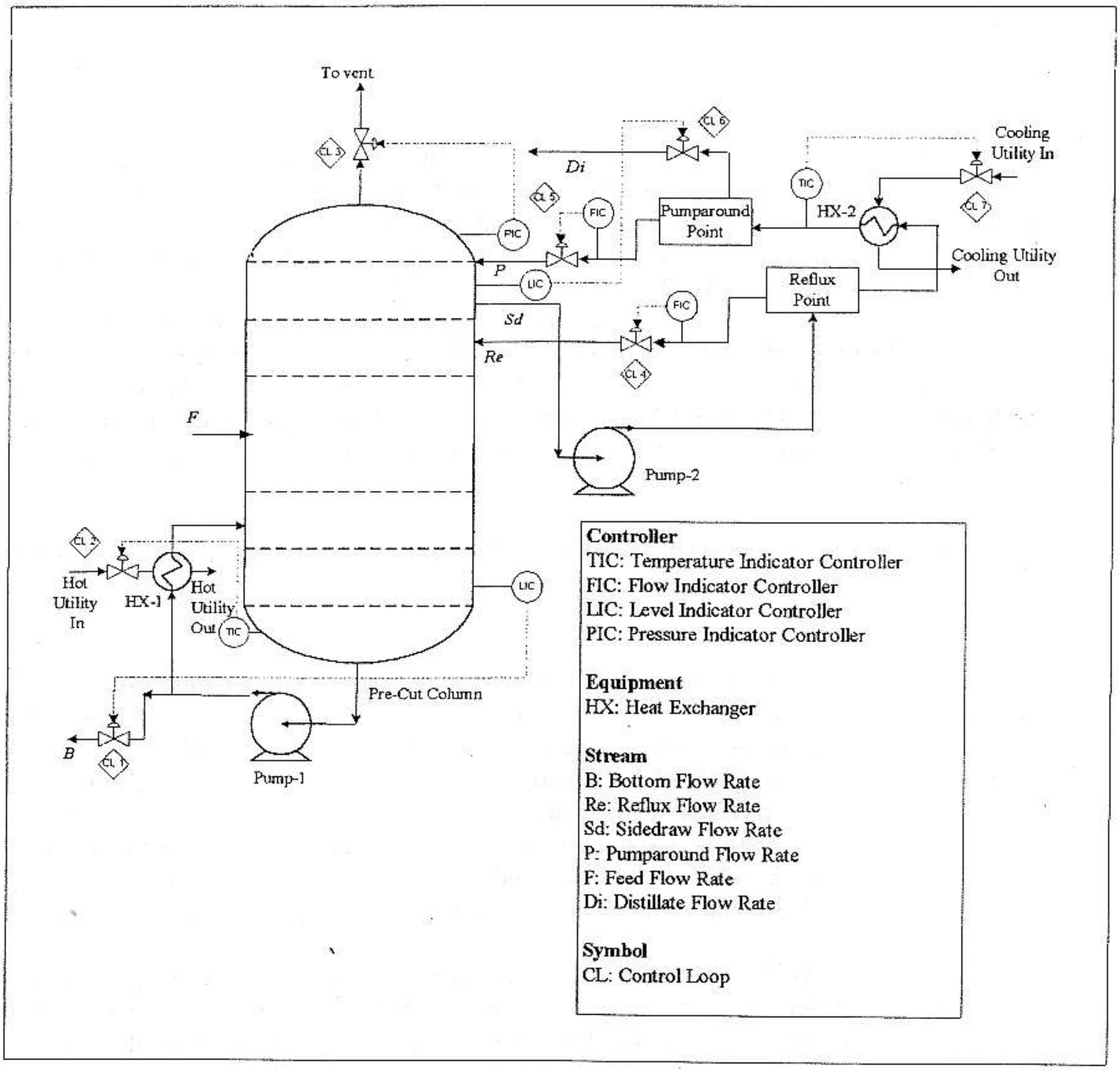
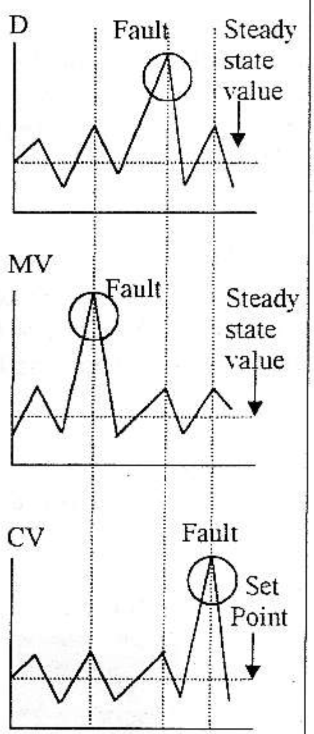
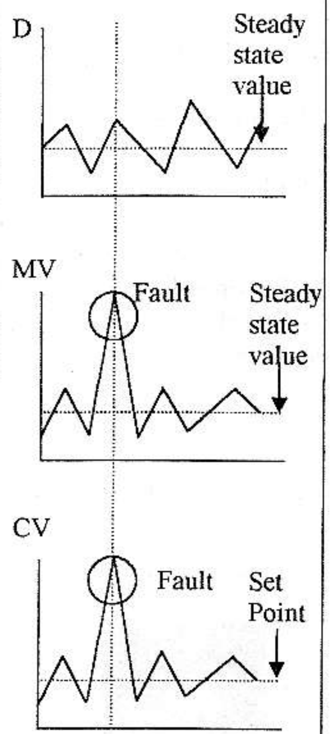
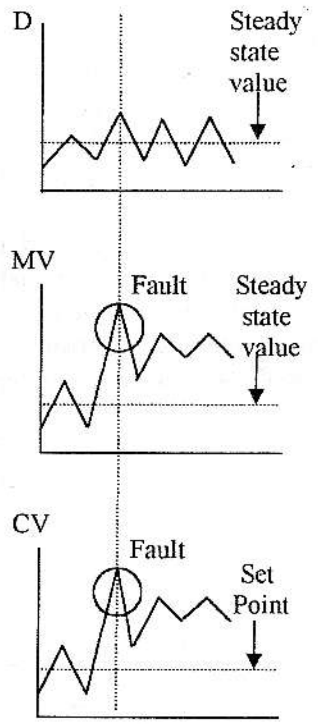


Figure 1: Distillation Column Model

The state equations for the distillation column were derived based on first principal equations. Ordinary Differential Equations (ODE) for state equations were formed and solved using 4th Order Runge-Kutta method. The MATLAB® software was used for the whole simulation program.

Based on the column model, two sets of process operating data were generated. For NOC data, some noises with zero mean were imbedded into the simulation program. The noises considered are small random change in selected key variables such as feed flow rate, feed temperature, reboiler duty, cooler duty and side draw flow rate. On the other hand, for OC data, some significant changes were purposely added into the process model as faults. These faults represent valve failures, sensor failures and controller malfunctions. The description of each type of fault is listed in Table1. The generated NOC and OC data are mean-centered and variance scaled. The NOC data will be subjected to multivariate analysis using PCA and PCorrA for deriving the correlation coefficients between the process variables and the selected quality variables.

Table 1: Fault Descriptions

Sensor Failure	Valve Failure	Controller Malfunction
• For open loop variables, only the value of the variable changes abnormally. For closed loop variables, only the value of the disturbance (D) OR the manipulated variable (MV) OR the control variable (CV) changes abnormally.	• For open loop variables, only the value of the variable changes abnormally. For closed loop variables, both the value of manipulated variable (MV) AND control variable (CV) changes abnormally together.	• For closed loop variables, the value of manipulated variable (MV) AND control variable (CV) changes abnormally together.
		

3.0 CORRELATION COEFFICIENTS OF NOC DATA

3.1 Correlation Coefficients Using PCA

Method for obtaining correlation coefficients, C_{ik}, using PCA was based on the work by Lam and Kamarul (2002b). Correlation coefficients using PCA are calculated as in Equation 1.

$$C_{ik} = \sum_{j=1}^{n} v_{ij} v_{kj} \lambda_j \qquad \text{(Eq. 1)}$$

Where: v_{ij}, v_{kj} = eigenvectors obtained from process data using PCA

λ_j = eigenvalue obtained from process data using PCA

3.2 Correlation Coefficients using PCorrA

Partial Correlation Analysis calculates the correlation between two variables while allowing the effect of other correlated variables on the two variables. For calculating correlation coefficient, C_{ik}, for variable 1 and 2 using PCorrA after allowing the effect of j-2 variables is as Equation 2.

$$C_{ik_{12}} = \frac{r_{12.(4,\ldots,j-2)} - r_{13.(4,\ldots,j-2)} r_{23.(4,\ldots,j-2)}}{(1 - r^2_{13.(4,\ldots,j-2)})^{1/2} (1 - r^2_{23.(4,\ldots,j-2)})^{1/2}} \qquad \text{(Eq.2)}$$

Where: r_{12} = correlation between variable 1 and 2
$r_{12.3}$ = partial correlation between variable 1 and 2 after the effect of variable 3
$r_{12.(3,4,\ldots,j-1)}$ = partial correlation between variable 1 and 2 after the effect of j-1 variables

4.0 PROCESS FAULT DETECTION USING C_{IK} BASED ON PCA AND PCorrA

C_{ik} relates a process variable, x_i with a quality variable, y_i in the following way:

$$y_i = C_{ik} x_i \qquad \text{(Eq.3)}$$

For conventional Shewhart Control Chart, the Upper Control Limit (UCL) and Lower Control Limit (LCL) for mean-centered and variance-scaled variables are +3 and -3 respectively (McNeese and Klein, 1991). Using the information from Equation 3, the UCL and LCL for quality variables and process variables will be +3 and -3 and $+3/C_{ik}$ and $-3/C_{ik}$ respectively. After the NOC control charts are established, they are used for fault detection of the OC data.

When a fault is detected, the variable of that control chart will be checked whether it is a closed loop variable or open loop variable. For open loop variable, the fault will be of sensor failure or valve failure as pre-designed while fault for closed loop variable can be of valve failure, sensor failure or controller malfunction. The performance of the fault detection method using correlation coefficients based on PCA and PCorrA is shown in Figure 2.

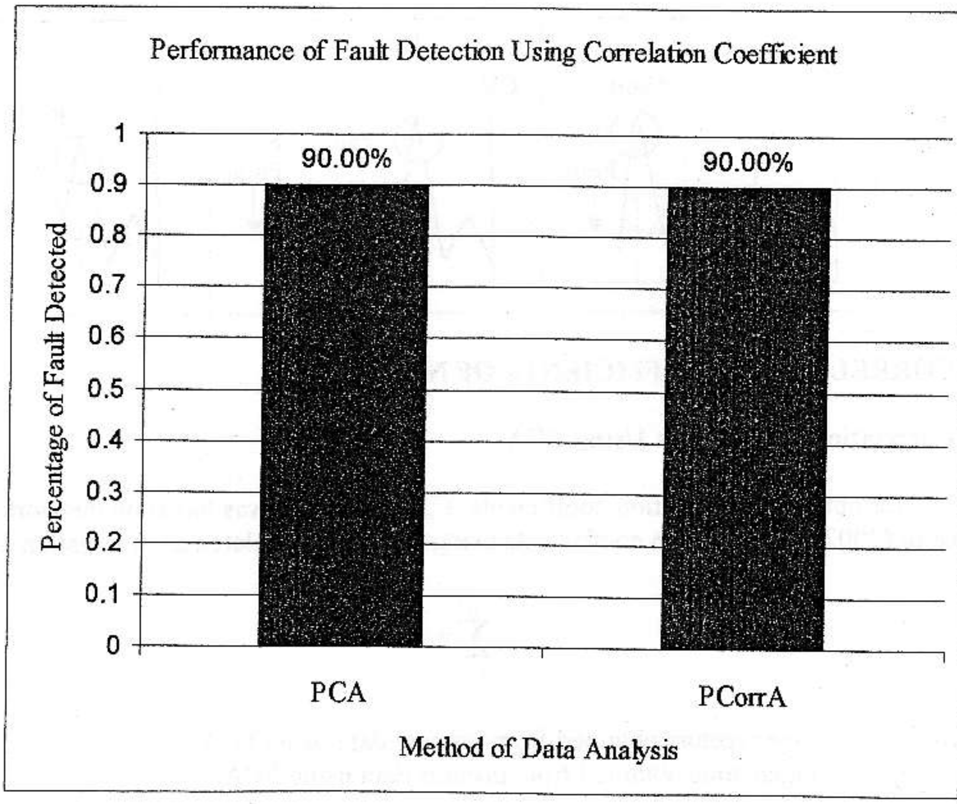


Figure 2: Performance of Fault Detection Using Correlation Coefficients

Both fault detection method using correlation coefficients based on PCA and PCorrA were able to detect the pre-designed faults. Out of the 10 faults in the fault data, 9 faults (both single fault and multiple faults) were successfully detected. These results show that the developed correlation coefficients were able to relate the key process variables to the quality variables of interest in the case study.

5.0 CONCLUSION

An approach for fault detection using correlation coefficients based on PCorrA and PCA was presented. The performance of the approach was studied on an industrial distillation column. The results show that the fault detection method using cross correlation coefficient was able to detect the faults present in the process. The cause of each fault can be diagnosed by checking the control charts of the key process variables in which a fault is detected. Fault diagnosis using method based on correlation coefficients is a research problem for future work.

6.0 NOTATION

C_{ik}: Correlation Coefficient
CV: Control variable
D: Disturbance
LCL: Lower Control Limit
MSPC: Multivariate Statistical Process Control
MV: Manipulated variable
NOC: Normal Operating Condition
OC: Out of control
ODE: Ordinary Differential Equation
PCorrA: Partial Correlation Analysis
PCA: Principal Component Analysis
v_{ij}, v_{kj}: Eigenvectors obtained from process data using PCA
UCL: Upper Control Limit
x: Process variable
y: Quality variable
λ_j: Eigenvalue obtained from process data using PCA

7.0 ACKNOWLEDGEMENTS

National Science Fellowship (NSF) scholarship is gratefully acknowledged.

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